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(54) **TISSUE SURFACE ROUGHNESS QUANTIFICATION BASED ON IMAGE DATA AND DETERMINATION OF A PRESENCE OF DISEASE BASED THEREON**

QUANTIFIZIERUNG DER RAUHEIT VON GEWEBEOBERFLÄCHEN AUF BASIS VON BILDDATEN UND DARAUF BASIERENDE BESTIMMUNG DES VORHANDENSEINS EINER KRANKHEIT

QUANTIFICATION DE LA RUGOSITÉ D'UNE SURFACE TISSULAIRE À BASE DES DONNÉS D'IMAGE ET DÉTERMINATION DE LA PRÉSENCE D' UNE MALADIE BASÉE LA-DESSUS

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Description

[0001] The following generally relates to quantifying a roughness of a surface of tissue in image data and determining a presence (or absence) of a disease of the tissue based thereon, and is described with particular application to computed tomography (CT). However, the following is also amenable to imaging modalities such as X-ray, magnetic resonance imaging (MRI), volumetric C-arm scanner and/or other imaging modality.

[0002] A typical computed tomography (CT) scanner has included an x-ray tube mounted on a rotatable gantry opposite a detector. The x-ray tube rotates around an examination region and emits polychromatic radiation that traverses the examination region and a subject and/or object disposed therein. The detector array detects radiation that traverses the examination region and produces a signal indicative thereof. A reconstructor reconstructs the signal and generates volumetric image data indicative of the subject and/or object disposed in the examination region. One or more images can be generated from the volumetric image data.

[0003] Disease of certain tissue/organs of the human body results in replacement of normal healthy tissue with fibrous tissue, which leads to a change in the surface shape of the tissue. For example, liver cirrhosis is a consequence of chronic liver disease, most commonly caused by alcoholism, hepatitis B and C and fatty liver disease. Liver cirrhosis is characterized by a replacement of normal healthy liver tissue by fibrosis, scar tissue and nodules of regenerated liver tissue. This remodeling leads to a change in the surface shape of the liver, and the surface of the liver, which is smooth for normal healthy tissue, starts to develop corrugations.

[0004] Chen et Al. in "An automatic diagnostic system for CT liver imager classification", IEEE Transactions on Biomedical engineering, vol.45 no. 6, 783-794, June 1998 relates to a CT liver image diagnostic classification system which will automatically find, extract the CT liver boundary and further classify liver diseases. It teaches using a Fractional Brownian Motion model in feature extraction to describe the roughness of nature surface.

[0005] US2012/177260 and US2011/172533 relate to diagnosis apparatus directed to detect liver irregularities though measurements of several parameters.

[0006] Image data (CT, MRI, etc.) based analysis has provided useful qualitative information. For example, the above noted remodeling can be visualized in image data generated by medical imaging modalities such as computed tomography (CT), magnetic resonance imaging (MRI), and/or other imaging modality. That is, the change in the surface shape of the liver and the corrugations can be visualized between an image with normal healthy liver tissue and diseased liver tissue through visual inspection and visual comparison of the images.

[0007] Unfortunately, such visual inspection consumes clinician time, which could otherwise be spent with patients, and relies on subjective determination of the clinician, and/or results of other tests (e.g., biopsy, etc.) prescribed based on the visual inspection, to determine a presence or absence of the disease. In view of the above, there exists an unresolved need for other approaches to detecting surface changes and a presence or absence of a disease of the tissue of interest based thereon.

[0008] Aspects described herein address the above-referenced problems and others.

[0009] Described herein is an approach to identify a presence (or absence) of tissue disease based on a quantification of a roughness of a surface of the tissue represented in imaging data.

[0010] In one aspect, an image data processor includes a surface roughness quantifier that generates a metric that quantifies a roughness of a surface of a tissue of interest in 3D image data based on a surface model adapted to the tissue of interest in the 3D image data and a decision component that generates a value signal indicating a presence or an absence of disease in the tissue of interest based on the metric.

[0011] In another aspect, a method includes generating a metric that quantifies a roughness of a surface of a tissue of interest in 3D image data based on a surface model adapted to the tissue of interest in the 3D image data, and generating a value signal indicating a presence or an absence of disease in the tissue of interest based on the metric.

[0012] In another aspect, a method includes generating a value that quantifies a roughness of a surface of the liver represented in 3D image data based on a surface model adapted to the liver in the 3D image data, wherein the value directly determines a presence or absence of disease of the liver.

[0013] The invention may take form in various components and arrangements of components, and in various steps and arrangements of steps. The drawings are only for purposes of illustrating the preferred embodiments and are not to be construed as limiting the invention.

FIGURE 1 schematically illustrates an image data processor in connection with an imaging system and a data repository.

FIGURE 2 schematically illustrates an example of the image data processor of FIGURE 1.

FIGURE 3 schematically illustrates another example of the image data processor of FIGURE 1.

FIGURE 4 schematically illustrates an example of method in accordance with the image data processor of FIGURE 1.

[0014] The following describes an approach to quantify tissue disease based on a roughness of a surface of the tissue represented in image data and identify a presence (or absence) of the disease in the tissue based thereon.

[0015] With reference to FIGURE 1, an imaging system 100 includes a computed tomography (CT) scanner, which includes a generally stationary gantry portion 102

and a rotating gantry portion 104. (As discussed herein, a MRI, X-ray, or other imaging modality could alternatively be employed.) The rotating gantry portion 104 is rotatably supported by the generally stationary gantry portion 102 via a bearing (not visible) or the like.

[0016] A radiation source 106, such as an x-ray tube, is supported by the rotating gantry portion 104 and rotates therewith around an examination region 108 about a longitudinal or z-axis. A detector array 110 subtends an angular arc opposite the examination region 108 relative to the radiation source 106. The detector array 110 detects radiation that traverses the examination region 108 and generates a signal indicative thereof.

[0017] A subject support 112 supports a subject or object in the examination region 108. An operator console 114 facilitates user interaction with the scanner 100. A reconstructor 116 reconstructs the signal, generating volumetric (3D) image data indicative of the scanned subject or object. The signal and/or reconstructed image data can be stored in a data repository 118, such as picture archiving and communication system (PACS), a radiology information system (RIS), a hospital information system (HIS), etc.

[0018] An image data processor 120 processes image data from the imaging system 100, the data repository 118, and/or other device. Such processing includes quantifying a roughness of a tissue of interest in the image data and determining, based on the quantified roughness, a presence or absence of disease. Such processing can be used to identify a presence or absence of cirrhosis in liver tissue and/or other disease in other tissue. This can be achieved without using a statistical model that employs a random variable to determine a likelihood of disease.

[0019] As described in greater detail below, in one non-limiting instance, such processing includes localizing the tissue of interest in 3D image data (e.g., via segmentation with a model or otherwise), performing coarse and/or refine delineation of a surface of the localized tissue of interest, and analyzing the delineated surface based on surface corrugations (e.g., amplitude, frequency, wavelength, distribution, etc.) using predetermined thresholds, predetermined patterns, etc. A non-limiting example of a suitable pattern includes surface patches, such as gray value pattern variations that may vary across a surface of an organ, in the image data of patients with a classified disease state. Where a catalog of such patterns is available, the pattern from the catalog that is closest to the delineated surface is selected and utilized to identify the disease state.

[0020] The image data processor 120 can be implemented via one or more microprocessors of one or more computers that execute one or more computer readable instructions. In one instance, the one or more computer readable instructions are encoded on computer readable storage medium such a physical memory and/or other non-transitory medium. Additionally or alternatively, at least one of the computer readable instructions can be carried by a carrier waver, a signal and/or other transitory medium.

[0021] FIGURE 2 schematically illustrates an example of the image data processor 120. As discussed above, the data processor 120, receives as input, 3D imaging data.

[0022] A tissue of interest (TOI) identifier 202 identifies a tissue of interest in the imaging data. Identification can be based on the scan protocol (e.g., liver scan), a user input, and/or other information.

[0023] A tissue of interest (TOI) segmentor 204 segments the tissue of interest from the imaging data. Known and/or other segmentation, including fully automatic and/or semiautomatic requiring user interaction, approaches are contemplated herein. By way of non-limiting example, in one instance, a model based organ segmentation is employed. Organ based models have been available as pre-defined triangulated surface models, which have been trained on medical image data sets from different modalities. Coarse and/or refined models are contemplated herein.

[0024] With such a model, a surface model can be initially positioned in the 3D imaging data. Then, the surface model is (automatically and/or semi-automatically) adapted to the surface of the tissue organ of interest based on an external energy term based on image features and an internal energy term which carries the predefined shape of the organ and its possible deformations to fit a large patient population. Other approaches are also contemplated herein. For example, a fully manual approach can be employed in which the user manually segments the tissue of interest.

[0025] A surface roughness quantifier 206 quantifies a surface roughness of the tissue of interest based on how the surface model is adapted to the surface of the organ. In one instance, the roughness is determined by starting from a position of each triangle on the surface model and calculating a position variation of a typical contrast gradient with respect to a mean surface position along a direction normal to the model surface. The mean surface position can be determined by the initial surface model adaptation.

[0026] In this example, a mathematical integral of the position variance of this gradient normalized to a total tissue of interest surface provides a quantitative measure for the surface roughness. Local roughness measures can also be determined. For example, the number of surface triangles of the base model can be increased until the variation of the surface is well captured by a refined model. Then, the refined model can be compared with the initial model to provide a more local measure of roughness.

[0027] A decision component 208 compares the roughness values to a predetermined threshold 210. Where a roughness value exceeds the threshold, the decision component 208 generates a first value signal indicative thereof (thereby directly determining the presence of the disease), and where a roughness value does

not exceed the threshold, the decision component 208 generates a second value signal indicative thereof. The values may also provide information about a stage of the disease, where the disease is present, i.e., by comparing against different thresholds, the decision component can generate an output related to the disease stage. The first and/or second value signal can be displayed in connection with the image data and/or otherwise to provide a visual metric that indicates whether the disease is present.

[0028] Additionally or alternatively, the surface roughness quantifier 206 determines a spatial position variation of at least one of an amplitude, a wavelength, or a frequency and/or a distribution of the amplitude on the surface as a function of at least one of wavelength or frequency, and the decision component 208 compares the spatial position variation and/or the distribution to a corresponding predetermined threshold to make the determination. For instance, the surface roughness quantifier 206 can perform a frequency analysis of the spatial position variation relative to a position of a mean position (smooth mesh) of the adapted surface model. Again, the decision component 208 generates the first value signal where the variation satisfies the threshold and generates the second value signal where the variation does not satisfy the threshold.

[0029] In FIGURE 3, the surface roughness quantifier 206 compares the adapted surface model to predetermined patterns 302, such as gray value pattern variations, and identifies a pattern with the strongest correlation to the adapted surface model. For example, with respect to particular tissue such as the liver, the adapted surface model can be compared with gray value pattern variations, stored in a database or the like, which may occur at the surface of the liver when liver cirrhosis is in different stages and may vary across the surface. These patterns are adapted locally to the surface, and the pattern with the strongest correlation to the surface model is identified. The decision component 208 compares the identified pattern to a pattern-to-stage map 304. The decision component 208 generates a value signal indicative of the mapping. The mapping indicates, at least, whether the disease is present in the tissue of interest, and can provide information about a stage of the disease, where the disease is present.

[0030] The value signal can be displayed in connection with the image data and/or otherwise to provide a visual metric that indicates whether the disease is present in the tissue of interest. By way of example, in one instance the value signal is presented in a visualization of the roughness on the surface, for example, as a 3D color-coded surface rendering.

[0031] In another embodiment, the image data processor 120 includes a combination of FIGURE 2 and 3 and/or other approaches to determining the roughness of the surface.

[0032] FIGURE 4 illustrate methods for determining a presence or absence of disease in a tissue of interest.

[0033] It is to be appreciated that the ordering of the acts is not limiting. As such, other orderings are contemplated herein. In addition, one or more acts may be omitted and/or one or more additional acts may be included.

[0034] At 402, 3D image data is obtained. Such image data can be obtained from the imaging system 100, another imaging system, the date repository 118, other date repository, and/or other device.

[0035] At 404, a tissue of interest is identified. Generally, the tissue of interest in this example is organ tissue that develops a surface roughness when diseased, relative to the a surface of the organ when disease is absent. A non-limiting example is liver tissue, in which liver cirrhosis is characterized by a replacement of normal healthy liver tissue by fibrosis, scar tissue and nodules of regenerated liver tissue.

[0036] At 406, the identified tissue of interest is segmented from the obtained 3D imaging data. As discussed herein, known and/or other segmentation techniques can be applied to segment the tissue of interest.

[0037] At 408, a quantitative roughness measure of a surface of the tissue of interest is determined from the segmented imaging data. As discussed herein, the quantitative roughness measure can be based on amplitude, frequency, wavelength, patterns, etc. of corrugations on the surface of the tissue of interest.

[0038] At 410, the quantitative roughness measure is used to determine a presence or absence of a disease. As discussed herein, this can be achieved by comparing the quantitative roughness measure to predetermined thresholds, patterns, and/or other information derived from previous studies of subject with and without the disease.

[0039] At 412, a value signal, indicative of whether the disease is presence or absence, is generated. As discussed herein, the value signal may also indicate a stage of a disease where it is determined that a disease is present.

[0040] At 414, optionally, the value signal is visually presented. As discussed herein, this includes visually displaying the value signal along with the image data and/or the segmented image data.

[0041] The above methods may be implemented by way of computer readable instructions, encoded or embedded on computer readable storage medium, which, when executed by a computer processor(s), cause the processor(s) to carry out the described acts. Additionally or alternatively, at least one of the computer readable instructions is carried by a signal, carrier wave or other transitory medium.

Claims

1. An image data processor (120), comprising:

a surface roughness quantifier (206) that generates a metric that quantifies a roughness of a

surface of a tissue of interest in 3D image data based on a surface model adapted to the tissue of interest in the 3D image data, wherein the model includes a pre-defined triangulated surface which is adapted to the surface of the issue of interest, wherein the surface roughness quantifier is adapted to calculate a position variation of a pre-defined contrast gradient with respect to a mean surface position along a direction normal to the model surface and to determine an integral of a local position variance of the gradient, normalized to a total tissue of interest surface, thereby generating the metric; and
a decision component (208) that generates a value signal indicating a presence or an absence of disease in the tissue of interest based on the metric.

2. The image data processor of claim 1, wherein the mean surface position is determined by an initial surface model adaptation.

3. The image data processor of any of claims 1 to 2, wherein the position variation pattern indicates a stage of the disease.

4. The image data processor of any of claims 1 to 3, wherein the surface roughness quantifier determines one or more of a spatial position variation of at least one of an amplitude, a wavelength, a frequency or a distribution of the amplitude on the surface as a function of at least one of wavelength or frequency, and the decision component compares the spatial position variation to a corresponding predetermined threshold to make the determination.

5. The image data processor of claim 1, wherein surface roughness quantifier compares the adapted surface model to predetermined patterns and identifies a pattern with the strongest correlation to the adapted surface model, and the decision component compares the identified pattern to a pattern-to-stage map and generates a value signal indicative of the mapping, wherein the mapping indicates whether the disease is present or absent.

6. The image data processor of claim 5, wherein the identified pattern indicates a stage of the disease.

7. The image data processor of any of claims 1 to 6, wherein the surface roughness quantifier adapts the model to the surface of the tissue of interest based on an external energy term and an internal energy term.

8. The image data processor of claim 7, wherein the external energy term is based on images features and the internal energy term includes a predefined shape of the tissue of interest.

9. The image data processor of any of claims 1 to 2, wherein the pre-defined triangulated surface is trained on medical image data sets from different modalities.

10. A method, comprising:

generating a metric that quantifies a roughness of a surface of a tissue of interest in 3D image data based on a surface model adapted to the tissue of interest in the 3D image data; and
generating a value signal indicating a presence or an absence of disease in the tissue of interest based on the metric,
wherein the model includes a pre-defined triangulated surface which is adapted to the surface of the tissue of interest, and further comprising:

calculating a position variation of a pre-defined contrast gradient with respect to a mean surface position along a direction normal to the model surface; and
determining an integral of a local position variance of the gradient, normalized to a total tissue of interest surface, thereby generating the metric.

11. The method of claim 10, wherein the generating the metric and the value signal do not include using a statistical model in which the roughness is a random variable.

12. The method of claim 10, further comprising:

increasing a number of surface triangles of the model, creating a refined model; and
comparing the refined model to the model to determine a more localized metric.

13. The method of any of claims 10 to 12, further comprising:

determining a spatial position variation of at least one of a wavelength, a frequency of a distribution of the roughness; and
comparing the spatial position variation to a corresponding predetermined threshold to determine the presence or absence of the disease.

14. The method of any of claims 10 to 13, further comprising:

comparing the adapted surface model to predetermined patterns;
identifying a pattern of the predetermined patterns with a strongest correlation to the adapted

surface model;
comparing the identified pattern to a pattern-to-stage map; and
identifying a map coorespoinding ot the identified pattern, wherein the map indicates the presence or absence of the disease.

15. The method of claim 14, wherein the map indicates a stage of the disease.

Patentansprüche

1. Bilddatenprozessor (120), umfassend:

einen Oberflächenrauheitsquantifizierer (206), der eine Metrik erzeugt, die eine Rauheit einer Oberfläche eines Gewebes von Interesse in 3D-Bilddaten auf Basis eines Oberflächenmodells quantifiziert, das an das Gewebe von Interesse in den 3D-Bilddaten angepasst ist, wobei das Modell eine vordefinierte triangulierte Oberfläche enthält, die an die Oberfläche des Punkts von Interesse angepasst ist, wobei der Oberflächenrauheitsquantifizierer angepasst ist, eine Positionsvariation eines vordefinierten Kontrastgradienten in Bezug auf eine mittlere Oberflächenposition entlang einer Richtung normal zur Modelloberfläche zu berechnen und ein Integral einer lokalen Positionsvarianz des Gradienten, normalisiert zu einer Gesamtgewebeoberfläche von Interesse zu bestimmen, wodurch die Metrik erzeugt wird; und
eine Entscheidungskomponente (208), die ein Wertsignal, das ein Vorhandensein oder ein Fehlen einer Krankheit in dem Gewebe von Interesse angibt, auf Basis der Metrik erzeugt.

2. Bilddatenprozessor nach Anspruch 1, wobei die mittlere Oberflächenposition durch eine anfängliche Oberflächenmodellanpassung bestimmt wird.

3. Bilddatenprozessor nach einem der Ansprüche 1 bis 2, wobei das Positionsvariationsmuster eine Stufe der Krankheit angibt.

4. Bilddatenprozessor nach einem der Ansprüche 1 bis 3, wobei der Oberflächenrauheitsquantifizierer eine oder mehrere einer räumlichen Positionsvariation von mindestens einer von einer Amplitude, einer Wellenlänge, einer Frequenz oder einer Verteilung der Amplitude auf der Oberfläche als eine Funktion mindestens einer von Wellenlänge oder Frequenz bestimmt und die Entscheidungskomponente die räumliche Positionsvariation mit einem entsprechenden vorbestimmten Schwellenwert vergleicht, um die Bestimmung vorzunehmen.

5. Bilddatenprozessor nach Anspruch 1, wobei der Oberflächenrauheitsquantifizierer das angepasste Oberflächenmodell mit vorbestimmten Mustern vergleicht und ein Muster mit der stärksten Korrelation zum angepassten Oberflächenmodell identifiziert und die Entscheidungskomponente das identifizierte Muster mit einer Muster-zu-Stufe-Karte vergleicht und ein Wertsignal erzeugt, das die Abbildung angibt, wobei die Abbildung angibt, ob die Krankheit vorhanden ist oder fehlt.

6. Bilddatenprozessor nach Anspruch 5, wobei das identifizierte Muster eine Stufe der Krankheit angibt.

7. Bilddatenprozessor nach einem der Ansprüche 1 bis 6, wobei der Oberflächenrauheitsquantifizierer das Modell an die Oberfläche des Gewebes von Interesse auf Basis eines externen Energieterms und eines internen Energieterms anpasst.

8. Bilddatenprozessor nach Anspruch 7, wobei der externe Energieterm auf Bildermerkmalen basiert und der interne Energieterm eine vordefinierte Form des Gewebes von Interesse enthält

9. Bilddatenprozessor nach einem der Ansprüche 1 bis 2, wobei die vordefinierte triangulierte Oberfläche an medizinischen Bilddatensätzen aus verschiedenen Modalitäten trainiert wird.

10. Verfahren, umfassend:

Erzeugen einer Metrik, die eine Rauheit einer Oberfläche eines Gewebes von Interesse in 3D-Bilddaten auf Basis eines Oberflächenmodells quantifiziert, das an das Gewebe von Interesse in den 3D-Bilddaten angepasst ist; und
Erzeugen eines Wertsignals, das ein Vorhandensein oder Fehlen einer Krankheit in dem Gewebe von Interesse auf Basis der Metrik angibt, wobei das Modell eine vordefinierte triangulierte Oberfläche enthält, die an die Oberfläche des Gewebes von Interesse angepasst ist, und weiter umfassend:

Berechnen einer Positionsvariation eines vordefinierten Kontrastgradienten in Bezug auf eine mittlere Oberflächenposition entlang einer Richtung normal zur Modelloberfläche; und
Bestimmen eines Integrals einer lokalen Positionsvarianz des Gradienten, normalisiert zu einer Gesamtgewebeoberfläche von Interesse, wodurch die Metrik erzeugt wird.

11. Verfahren nach Anspruch 10, wobei das Erzeugen der Metrik und des Wertsignals kein Verwenden ei-

nes statistischen Modells enthalten, in dem die Rauheit eine Zufallsvariable ist.

12. Verfahren nach Anspruch 10, weiter umfassend:

Erhöhen einer Anzahl von Oberflächendreiecken des Modells, wodurch ein verfeinertes Modell geschaffen wird; und
Vergleichen des verfeinerten Modells mit dem Modell, um eine stärker lokalisierte Metrik zu bestimmen.

13. Verfahren nach einem der Ansprüche 10 bis 12, weiter umfassend:

Bestimmen einer räumlichen Positionsvariation von mindestens einer von einer Wellenlänge, einer Frequenz einer Verteilung der Rauheit; und Vergleichen der räumlichen Positionsvariation mit einem entsprechenden vorbestimmten Schwellenwert, um das Vorhandensein oder Fehlen der Krankheit zu bestimmen.

14. Verfahren nach einem der Ansprüche 10 bis 13, weiter umfassend:

Vergleichen des angepassten Oberflächenmodells mit vorbestimmten Mustern;
Identifizieren eines Musters der vorbestimmten Muster mit einer stärksten Korrelation zu dem angepassten Oberflächenmodell;
Vergleichen des identifizierten Musters mit einer Muster-zu-Stufe-Karte; und
Identifizieren einer Karte, die dem identifizierten Muster entspricht, wobei die Karte das Vorhandensein oder Fehlen der Krankheit angibt.

15. Verfahren nach Anspruch 14, wobei die Karte eine Stufe der Krankheit angibt.

Revendications

1. Processeur de données d'images (120) comprenant :

un quantificateur de rugosité de surface (206) qui génère une métrique qui quantifie une rugosité d'une surface d'un tissu d'intérêt dans des données d'images 3D sur la base d'un modèle de surface adapté au tissu d'intérêt dans les données d'images 3D, dans lequel le modèle comprend une surface triangulée prédéfinie qui est adaptée à la surface du tissu d'intérêt, dans lequel le quantificateur de rugosité de surface est à même de calculer une variation de position d'un gradient de contraste prédéfini par rapport à une position de surface moyenne le long d'une direction normale à la surface du modèle et déterminer une intégrale d'une variance de position locale du gradient normalisée sur une surface de tissu d'intérêt totale, générant de la sorte la métrique ; et
une composant de décision (208) qui génère un signal de valeur indiquant une présence ou une absence de maladie dans le tissu d'intérêt sur la base de la métrique.

2. Processeur de données d'images selon la revendication 1, dans lequel la position de surface moyenne est déterminée par une adaptation de modèle de surface initiale.

3. Processeur de données d'images selon l'une quelconque des revendications 1 à 2, dans lequel le motif de variation de position indique un stade de la maladie.

4. Processeur de données d'images selon l'une quelconque des revendications 1 à 3, dans lequel le quantificateur de rugosité de surface détermine une ou plusieurs d'une variation de position spatiale d'au moins l'une d'une amplitude, d'une longueur d'onde, d'une fréquence ou d'une distribution de l'amplitude sur la surface en fonction d'au moins l'une de la longueur d'onde ou de la fréquence et la composante de décision compare la variation de position spatiale à un seuil prédéterminé correspondant pour effectuer la détermination.

5. Processeur de données d'images selon la revendication 1, dans lequel le quantificateur de rugosité de surface compare le modèle de surface adapté à des motifs prédéterminés et identifie un motif avec la corrélation la plus forte avec le modèle de surface adapté et la composante de décision compare le motif identifié à une carte de motif-stade et génère un signal de valeur indicatif du mappage, dans lequel le mappage indique si la maladie est présente ou absente.

6. Processeur de données d'images selon la revendication 5, dans lequel le motif identifié indique un stade de la maladie.

7. Processeur de données d'images selon l'une quelconque des revendications 1 à 6, dans lequel le quantificateur de rugosité de surface adapte le modèle à la surface du tissu d'intérêt sur la base d'un terme d'énergie externe et d'un terme d'énergie interne.

8. Processeur de données d'images selon la revendication 7, dans lequel le terme d'énergie externe est basé sur des caractéristiques d'images et le terme d'énergie interne comprend une forme prédéfinie du

tissu d'intérêt.

9. Processeur de données d'images selon l'une quelconque des revendications 1 à 2, dans lequel la surface triangulée prédéfinie est formée sur des ensembles de données d'images médicales à partir de différentes modalités.

10. Procédé comprenant :

la génération d'une métrique qui quantifie une rugosité d'une surface d'un tissu d'intérêt en données d'images 3D sur la base d'un modèle de surface adapté au tissu d'intérêt dans les données d'images 3D ; et
la génération d'un signal de valeur indiquant une présence ou une absence de maladie dans le tissu d'intérêt sur la base de la métrique,
dans lequel le modèle comprend une surface triangulée prédéfinie qui est adaptée à la surface du tissu d'intérêt, et comprenant en outre :

le calcul d'une variation de position d'un gradient de contraste prédéfini par rapport à une position de surface moyenne le long d'une direction normale à la surface du modèle ; et
la détermination d'une intégrale d'une variance de position locale du gradient normalisée sur une surface totale de tissu d'intérêt, générant ainsi la métrique.

11. Procédé selon la revendication 10, dans lequel la génération de la métrique et du signal de valeur n'inclue pas l'utilisation d'un modèle statistique dans lequel la rugosité est une variable aléatoire.

12. Procédé selon la revendication 10, comprenant en outre :

l'augmentation d'un nombre de triangles de surface du modèle, créant un modèle raffiné ; et
la comparaison du modèle raffiné au modèle pour déterminer une métrique plus localisée.

13. Procédé selon l'une quelconque des revendications 10 à 12, comprenant en outre :

la détermination d'une variation de position spatiale d'au moins l'une d'une longueur d'onde, d'une fréquence ou d'une distribution de la rugosité ; et
la comparaison de la variation de position spatiale à un seuil prédéterminé correspondant pour déterminer la présence ou l'absence de la maladie.

14. Procédé selon l'une quelconque des revendications 10 à 13, comprenant en outre :

la comparaison du modèle de surface adapté à des motifs prédéterminés ;
l'identification d'un motif des motifs prédéterminés avec une corrélation la plus forte avec le modèle de surface adapté ;
la comparaison du motif identifié à une carte de motif-stade ; et
l'identification d'une carte correspondant au motif identifié, dans lequel la carte indique la présence ou l'absence de la maladie.

15. Procédé selon la revendication 14, dans lequel la carte indique un stade de la maladie.

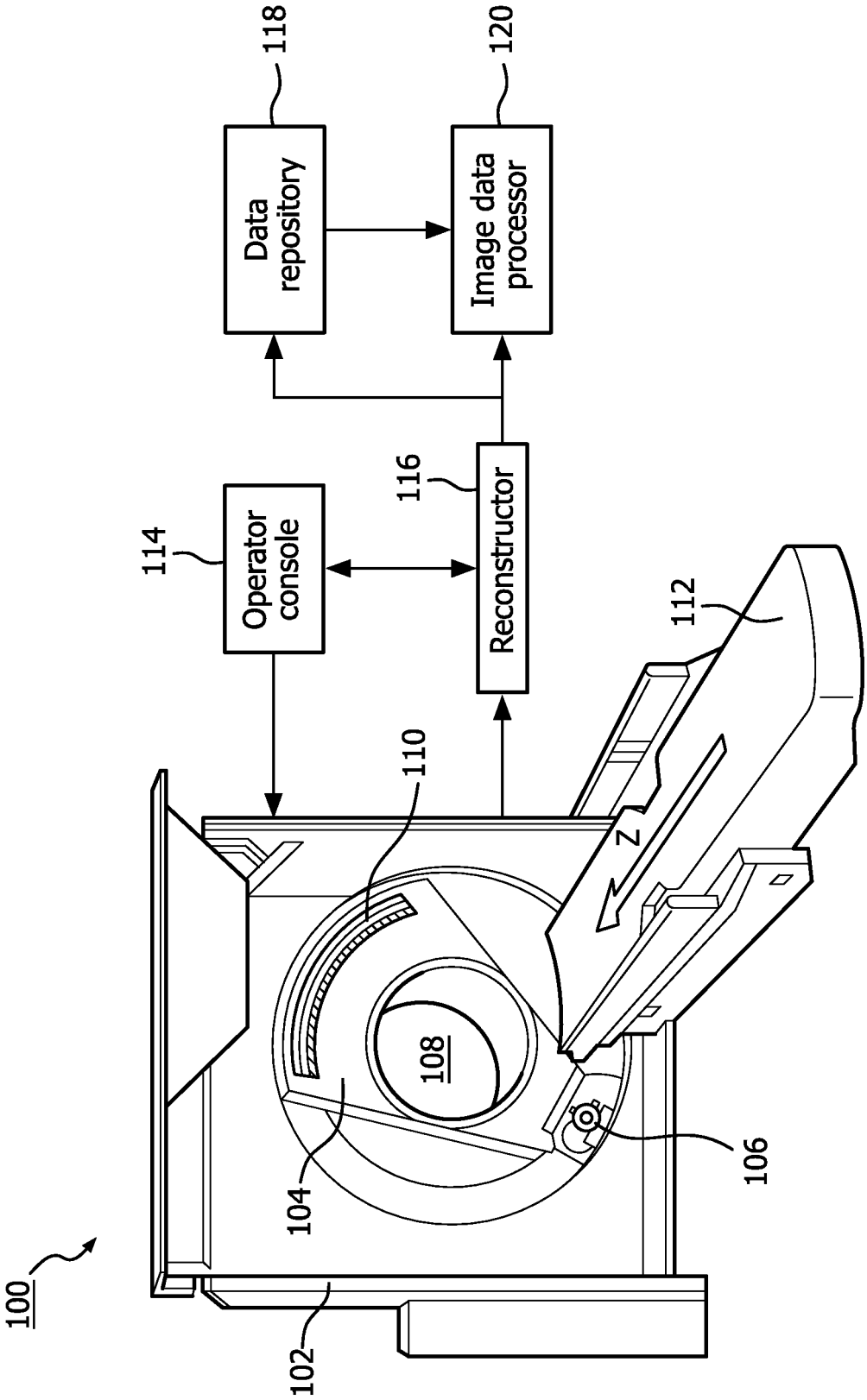
118
120
Data repository
Image data processor
116
114
Operator console
Reconstructor
112
110
Z
108
104
106
100
102

FIG. 1

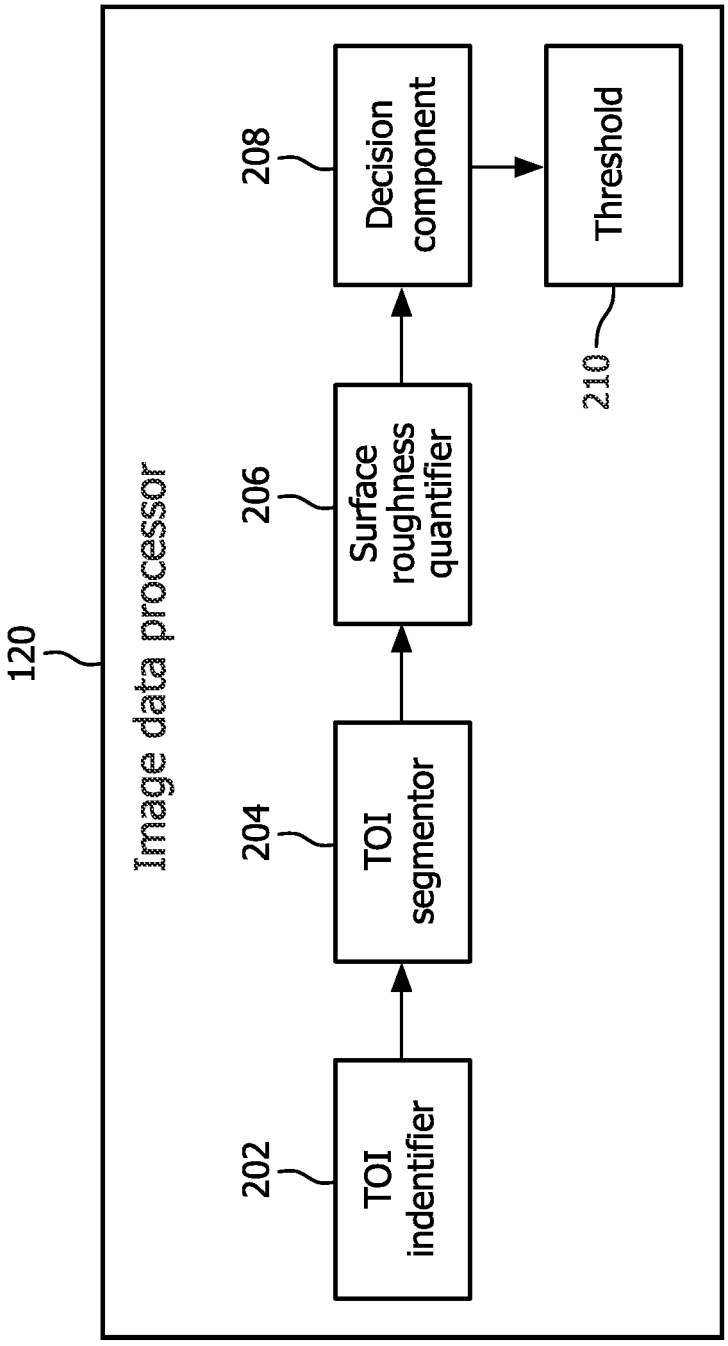
120
Image data processor
202
TOI indentifier
204
TOI segmentor
206
Surface roughness quantifier
208
Decision component
210
Threshold

FIG. 2

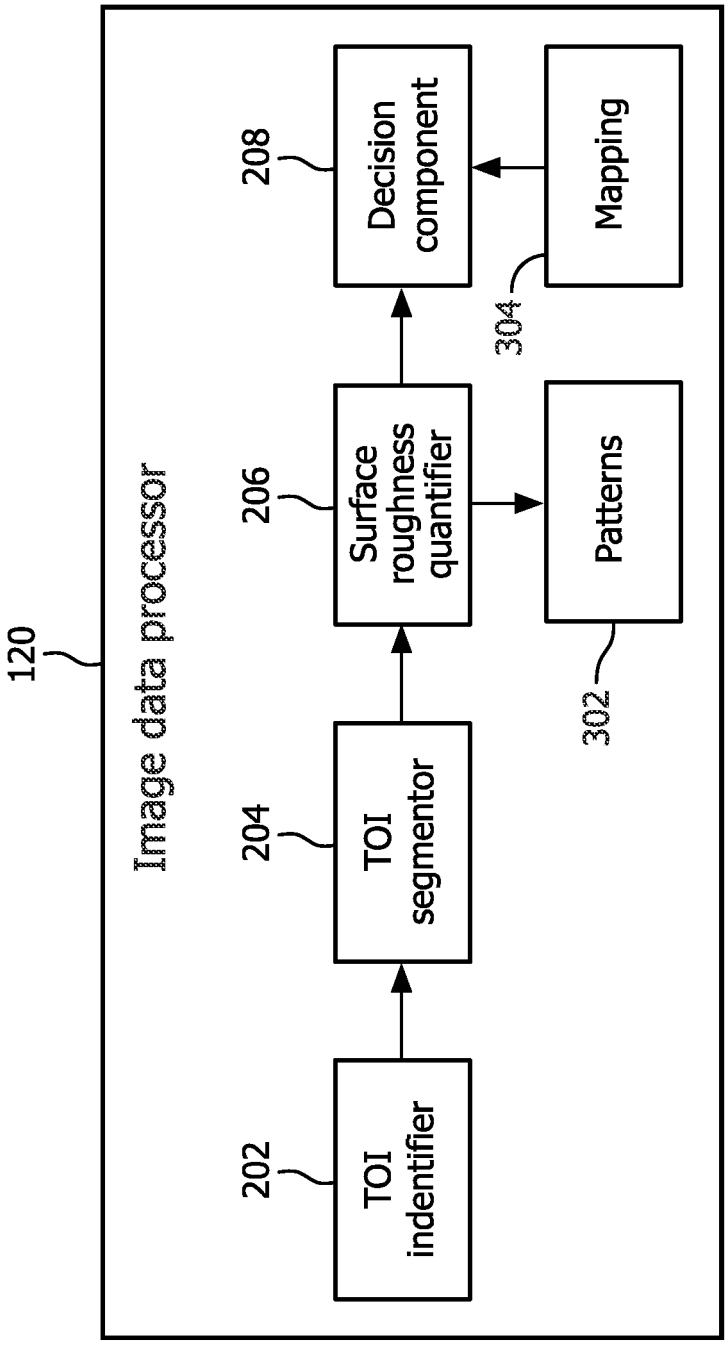
120
Image data processor
202
TOI indentifier
204
TOI segmentor
206
Surface roughness quantifier
208
Decision component
302
Patterns
304
Mapping

FIG. 3

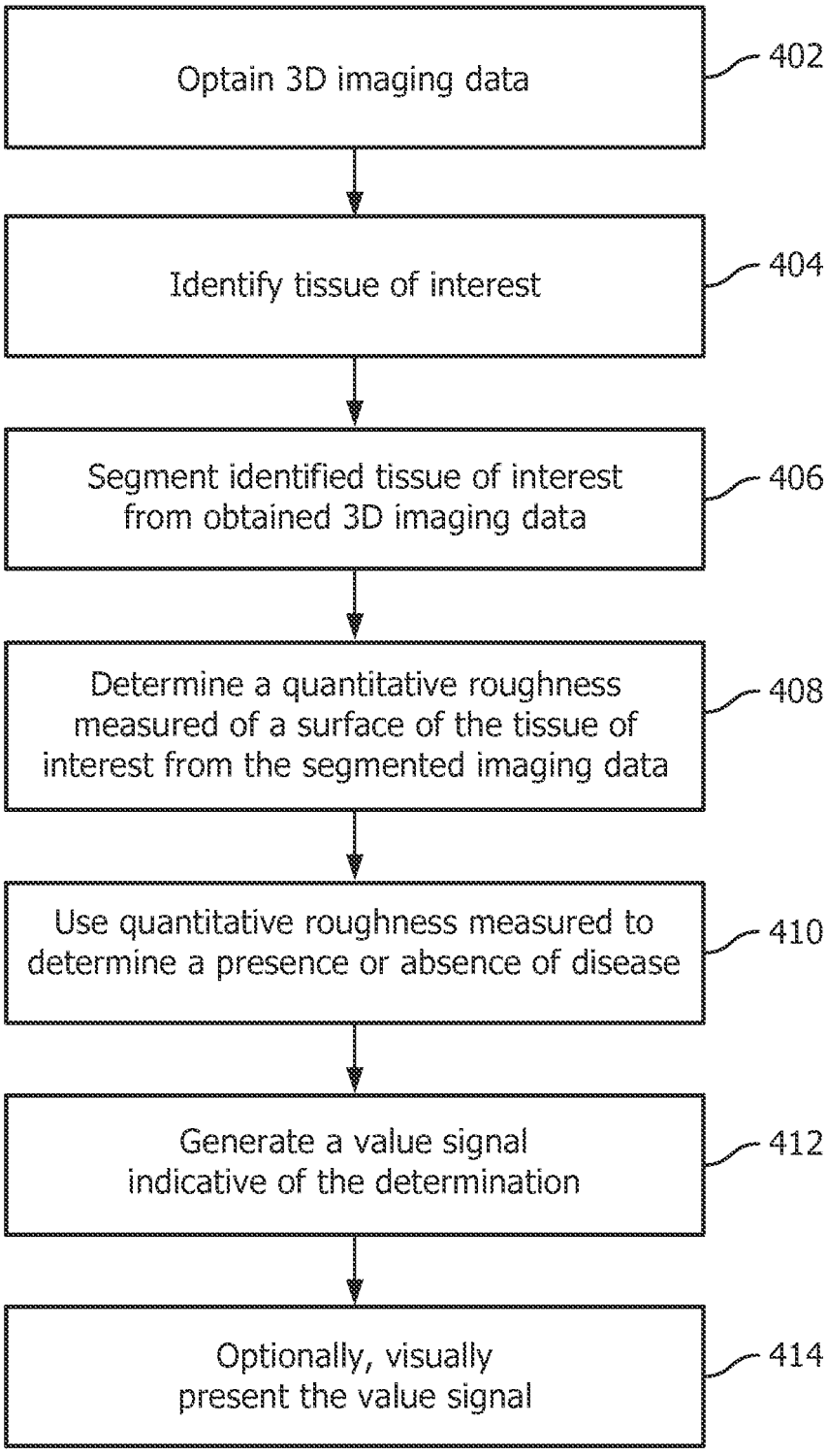
Optain 3D imaging data
402
Identify tissue of interest
404
Segment identified tissue of interest from obtained 3D imaging data
406
Determine a quantitative roughness measured of a surface of the tissue of interest from the segmented imaging data
408
Use quantitative roughness measured to determine a presence or absence of disease
410
Generate a value signal indicative of the determination
412
Optionally, visually present the value signal
414

FIG. 4

REFERENCES CITED IN THE DESCRIPTION

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Patent documents cited in the description

- US 2012177260 A **[0005]**
- US 2011172533 A **[0005]**

Non-patent literature cited in the description

- **CHEN et al.** An automatic diagnostic system for CT liver imager classification. *IEEE Transactions on Biomedical engineering,* June 1998, vol. 45 (6), 783-794 **[0004]**